AFRL-MN-EG-TP-2006-7413

REFLECTIVE AND POLARIMETRIC CHARACTERISTICS OF URBAN MATERIALS

Douglas G. Jones
Dennis H. Goldstein
Jonathan C. Spaulding
Air Force Research Laboratory
Munitions Directorate
AFRL/MNGI
Eglin AFB, FL 32542-6810

SEPTEMBER 2006

CONFERENCE PAPER

This paper was presented at the Defense and Security Symposium, Orlando, FL 17-21 April 2006. It will be published in the proceedings. The authors are U.S. Government employees working within the scope of their position. Therefore, this is a work of the U.S. Government and is not subject to copyright in the United States.

This paper is published in the interest of the scientific and technical information exchange. Publication of this paper does not constitute approval or disapproval of the ideas or findings.

AIR FORCE RESEARCH LABORATORY, MUNITIONS DIRECTORATE

- **Air Force Material Command**
- **United States Air Force**
- **Eglin Air Force Base**

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 0704-0188*

1. REPORT DATE *(DD-MM-YYYY)*	2. REPORT TYPE	3. DATES COVERED *(From - To)*
XX-09-2006	CONFERENCE PAPER	

4. TITLE AND SUBTITLE

Reflective And Polarimetric Characteristics Of Urban Materials

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER
62602F

6. AUTHOR(S)

Douglas G. Jones
Dennis H. Goldstein
Jonathan C. Spaulding

5d. PROJECT NUMBER
2068

5e. TASK NUMBER
30

5f. WORK UNIT NUMBER
45

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

Air Force Research Laboratory
Munitions Directorate
AFRL/MNGI
Eglin AFB, FL 32542-6810

8. PERFORMING ORGANIZATION REPORT NUMBER
AFRL-MN-EG-TP-2006-7413

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

Air Force Research Laboratory
Munitions Directorate
AFRL/MNGI
Eglin AFB, FL 32542-6810

10. SPONSOR/MONITOR'S ACRONYM(S)
AFRL-MN-EG

11. SPONSOR/MONITOR'S REPORT NUMBER(S)
SAME AS BLOCK 8

12. DISTRIBUTION/AVAILABILITY STATEMENT

DISTRIBUTION A: Approved for public release; distribution unlimited.
Approval Confirmation #AAC/PA 03-13-06-121

13. SUPPLEMENTARY NOTES

This paper was presented at the Defense and Security Symposium, Orlando, FL 17-21 April 2006. It will be published in the proceedings. The authors are U.S. Government employees working within the scope of their position. Therefore, this is a work of the U.S. Government and is not subject to copyright in the United States.

14. ABSTRACT

A spectropolarimetric reflectometer is used to measure the monostatic bidirectional reflectance distribution function (mBRDF) and the complete Mueller matrix of a number of urban type materials over a broad spectral region. Derivative features from these measurements are computed and stochastic models of each material are constructed. The models are then used to generate data for separability studies by implementation of a kernel-based linear discriminant classification technique. The purpose for this study, selection of materials, measurements process, analysis techniques, and concluding results are all presented.

15. SUBJECT TERMS

polarimetry, spectropolarimetry, Mueller matrix, bidirectional reflectance distribution function, urban material, pattern recognition, support vector machine

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
UNCLASSIFIED	UNCLASSIFIED	UNCLASSIFIED	SAR	12	Jonathan C. Spaulding
					19b. TELEPHONE NUMBER *(Include area code)*

Reflective and polarimetric characteristics of urban materials

Douglas G. Jones, Dennis H. Goldstein, Jonathan C. Spaulding
Air Force Research Laboratory, 101 West Eglin Blvd, Eglin AFB, BL 32542

ABSTRACT

A spectropolarimetric reflectometer is used to measure the monostatic bidirectional reflectance distribution function (mBRDF) and the complete Mueller matrix of a number of urban type materials over a broad spectral region. Derivative features from these measurements are computed and stochastic models of each material are constructed. The models are then used to generate data for separability studies by implementation of a kernel-based linear discriminant classification technique. The purpose for this study, selection of materials, measurements process, analysis techniques, and concluding results are all presented.

Keywords: polarimetry, spectropolarimetry, Mueller matrix, bidirectional reflectance distribution function, urban material, pattern recognition, support vector machine

1. BACKGROUND AND PURPOSE

Remote sensing is a broad and diverse subject. Sensors exist today that cover the entire electromagnetic spectrum and operate at ranges from nanometers to hundreds of kilometers. As sensor technologies mature, remote sensing applications are also growing rapidly. This includes topographical mapping, meteorological (weather and atmospheric) monitoring, natural resource surveying, agricultural crop analysis, and environmental assessment resulting from urban growth. In addition, there are many military applications that fall under the general category of surveillance and reconnaissance (e.g., battle damage assessment, troop movement monitoring, change detection, object or target recognition). For these and other applications, scientists are benefiting from the recent advancements in hyper-spectral, multi-spectral, and multi-channel sensor configurations.

The Advanced Guidance Division of the Air Force Research Laboratory's Munitions Directorate (AFRL/MN) is investigating sensing solutions for the purpose of target recognition from airborne platforms (e.g., aircraft, unmanned aerial vehicles, autonomous weapon systems). This includes studies of sensing modalities, feature selection, and pattern recognition methodologies. Of primary interest is the ability to sense and discriminate between the two broad classes of materials: natural and man-made. Additionally, it is desired to find suitable features that will allow for separating objects and materials within each of these classes. This is a very challenging problem especially when objects of interest are obscured. Also, it is desirable to distinguish among classes of similar objects when they are situated in a densely populated or urban environment. It is the latter problem that this study addresses by investigating the reflective and polarimetric signatures of a variety of materials prevalent in the urban environment.

Others have researched the reflective and polarimetric properties of urban materials[1] but few studies include a measurement of the complete Mueller matrix, and the material database is limited. A previous AFRL/MN study[2] was conducted to investigate similar characteristics of natural (e.g., soils, leaves, barks) materials. This paper extends that work to the urban environment. Additionally, statistical pattern recognition techniques are employed to characterize and quantify the separability among the material types. We call this a "material space" assessment. The measurements are also being used to develop a database for Irma[3]. Irma is capable of generating polarimetric synthetic imagery at any wavelength. Scenes can be constructed containing textured objects where the object material properties are drawn from the phenomenological measurement database. These synthetic scenes are used in similar studies at AFRL/MN to assess target recognition in the "image space."

2. MEASUREMENT PROCESS

The instrument used to measure the phenomenological (reflective and polarimetric) properties of materials is a dual rotating retarder spectropolarimeter[4] and is shown in Fig. 1. It can be configured to collect measurements in one of two modes: transmission or reflection. For this study we operate in the reflection mode. The spectropolarimeter is based around a commercial Fourier transform spectrometer: the Bio-Rad FTS-6000. It generates radiation from the ultraviolet to the far infrared, and is computer controlled through the Win-IR Pro software package. A Visual Basic program, Spectrotron, operates as an executive to provide control over the spectrometer, motorized rotation stages, and spectropolarimetric data processing. For purposes of the measurements collected here, the spectrometer is used with one source, a 150W tungsten-halogen lamp, and two detectors, a silicon detector for the near infrared (NIR) measurements (0.7 – 1.1 μm) and a mercury-cadmium-telluride detector for the short-wave infrared (SWIR) measurements (1.1 – 2.3 μm). The Bio-Rad spectrometer serves as the radiation source for the polarimetric portion of the instrument and is operated in the conventional absorption spectroscopy mode. The radiation generated by the spectrometer is brought out through the spectrometer's external port.

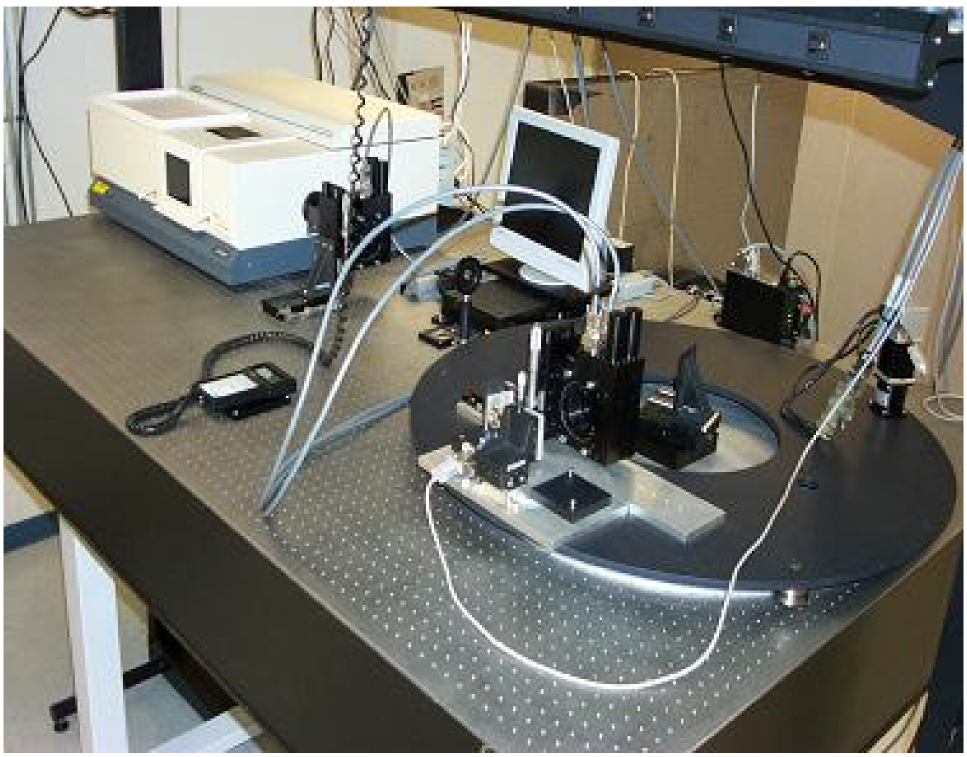


Figure 1. AFRL/MN EO Laboratory Fourier Transform spectropolarimeter.

Figure 2 shows the basic optical schematic of the instrument for monostatic reflection measurements. In this mode, the detector is fixed in the position shown and the sample is mounted on a computer-controlled motorized rotational stage. The sample can be rotated so that any in-plane incidence angle is obtained. The optical system that collects light for the detector consists of an off-axis parabolic mirror. This mirror is fixed to look toward the beamsplitter and focus light onto the detector that is mounted perpendicularly to the light coming from the beamsplitter. The parabolic mirror, detector, and mounting devices are referred to as the detector assembly. The sample is mounted vertically so that its surface comprises a vertical plane, and it may be rotated to any position around a vertical axis. Data collection proceeds by rotating the sample to a set of desired angles, and spectropolarimetric data are then collected at each sample angle. The instrument may be used for transmissive measurements as well by placing a transmissive sample on the sample rotation stage and lining up the detector assembly with the source beam on the far side of the sample. In order to obtain spectropolarimetric measurements, a dual rotating retarder Mueller matrix polarimeter, described by Azzam[5], is included in the system. This polarimeter consists of a polarization state generator (PSG) before the sample and a polarization state analyzer (PSA) after the sample. The PSG consists of a linear polarizer followed by a quarter wave retarder. The PSA consists of a quarter wave retarder followed by a linear polarizer and is located on the platter in front of the detector assembly. Although we use retarders that are nominally quarter wave in the spectral region being measured, the exact retardance is not critical. When the retarders are rotated in a five to one ratio, all sixteen elements of the sample Mueller matrix are encoded onto twelve harmonics of the detected signal, which can then be Fourier analyzed to recover the Mueller matrix elements. The reflectometer may be used without any modification of the polarization of the source radiation by removing the PSA and PSG assemblies. In this mode, the system is a spectral reflectometer and is the configuration used to collect the sample mBRDF measurements.

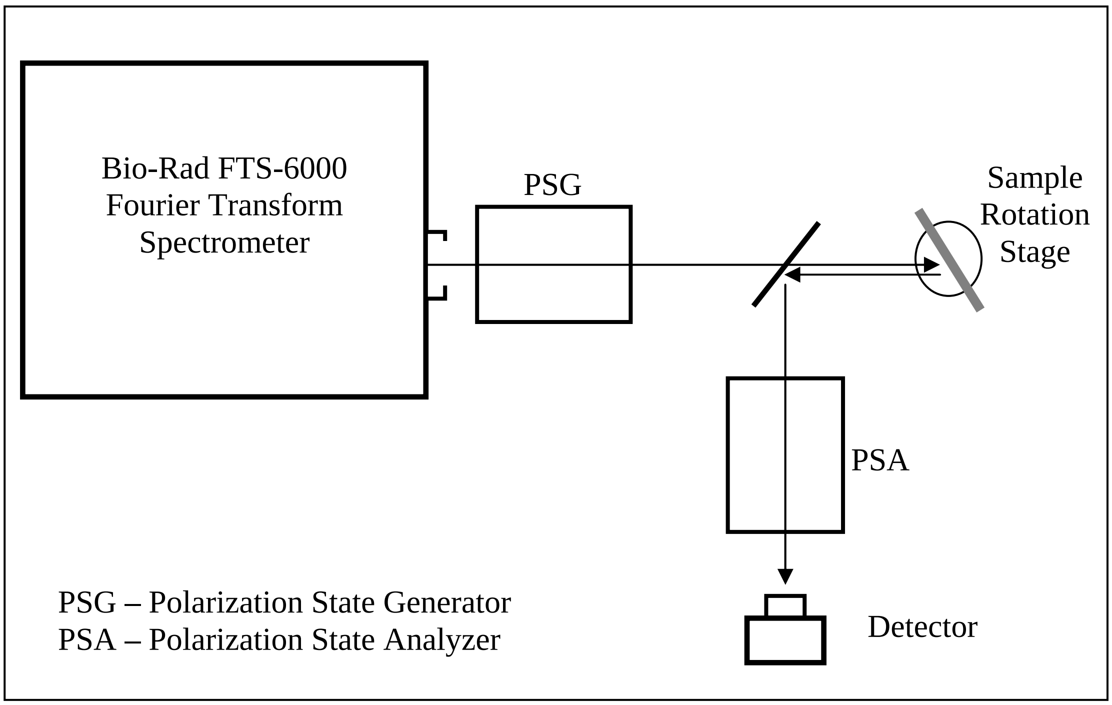


Figure 2. Spectropolarimeter configured for monostatic measurements.

The data reduction algorithm for this polarimeter, as originally presented by Azzam, assumes ideal polarization elements and no orientation errors. The data reduction algorithms may be generalized to compensate for systematic errors that result when orientation misalignment and non-ideal retarders are used. If the polarization elements are rotationally misaligned, or the retarders do not have exactly one-quarter wave of retardance, the changes in Fourier amplitudes and phases result in errors in the sample Mueller matrix. Even small orientation and retardance errors (< 1%) can lead to large errors in the measured Mueller matrix (> 10% in some matrix elements). These errors become especially important when the retardance and alignment vary significantly from their nominal values such as in multi-wavelength or spectral instruments. We have incorporated correction terms for orientation and retardance errors into the dual rotating retarder data reduction algorithm as described in Chenault[6] et al.

3. MATERIAL SELECTION AND MEASUREMENT RESULTS

For this study, we derive discriminant properties based on the reflective and polarimetric characteristics of several urban materials. Six samples were selected for analysis: rubber, shingle, plywood, drywall (sheetrock) front side, brick, and concrete. Photographs of the test samples are shown in Fig. 3.

(a) rubber (b) shingle

(c) plywood (d) drywall front side

(e) brick (f) concrete

Figure 3. Material selection.

For each sample, the mBRDFs and Mueller matrices were measured from 0.7 to 2.3 μm at 1290 distinct frequencies, each separated by wavenumbers of approximately 16 cm^{-1}. Each sample is measured at 18 incidence angles (relative to the source) from -10° to +60° with finer resolution near normal incidence (-10°, -8°, -6°, -4°, -2°, -1°, 0°, 1°, 2°, 4°, 6°, 8°, 10°, 15°, 20°, 30°, 45°, 60°). The mBRDFs for all materials are shown in Fig. 4. The Mueller matrix data cube for one sample (drywall) is shown in Fig. 5. A wavelength slice into the Mueller matrix data at normal incidence angle for all samples is illustrated in Fig. 6.

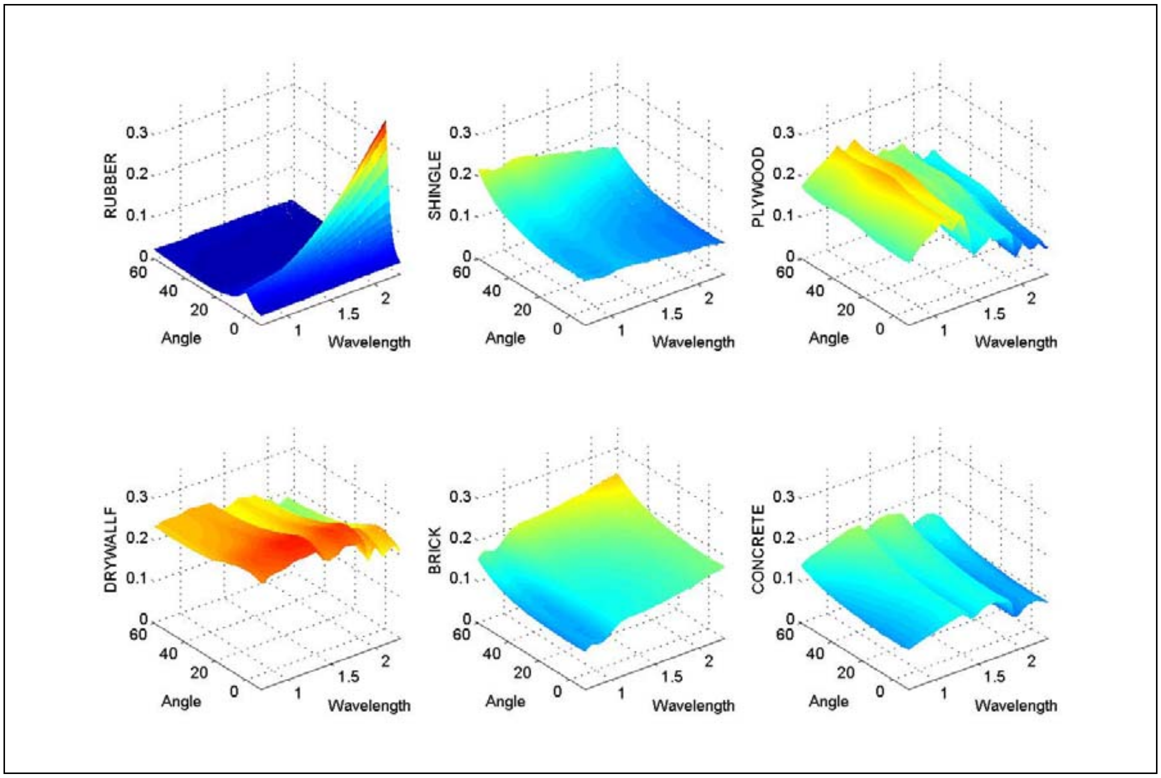


Figure 4. mBRDFs for all materials.

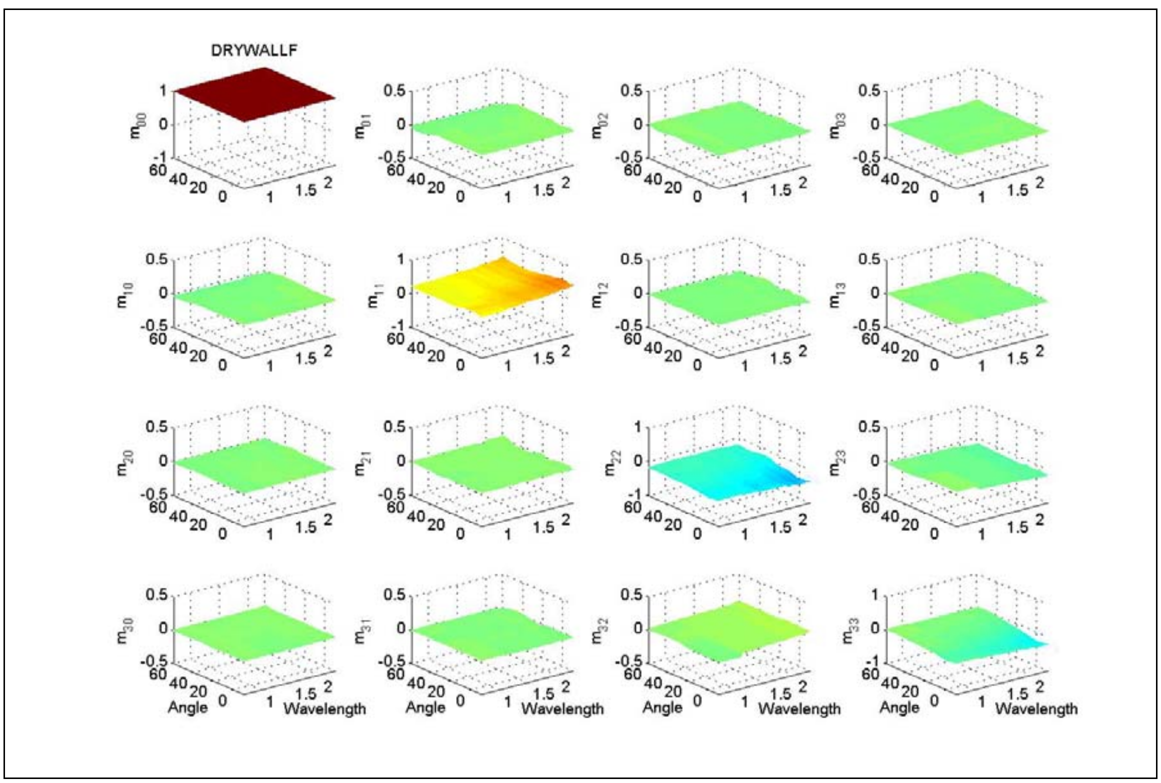
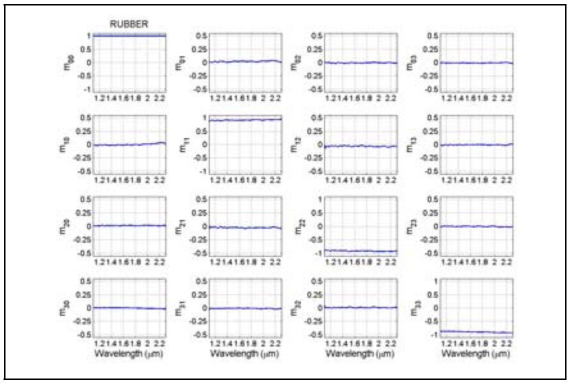
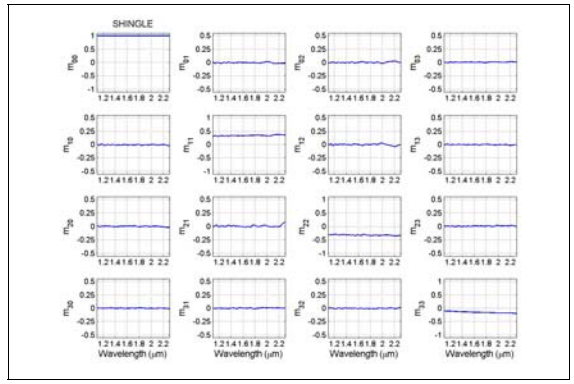


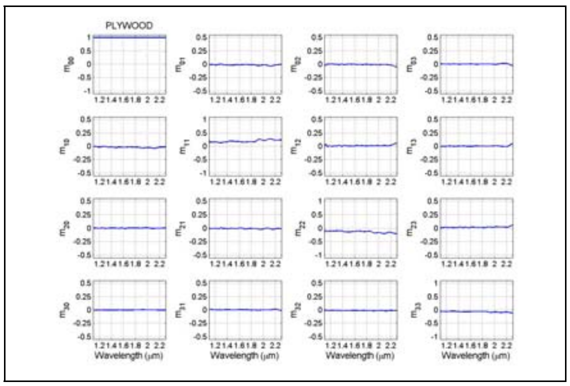
Figure 5. Mueller matrices for drywall sample.



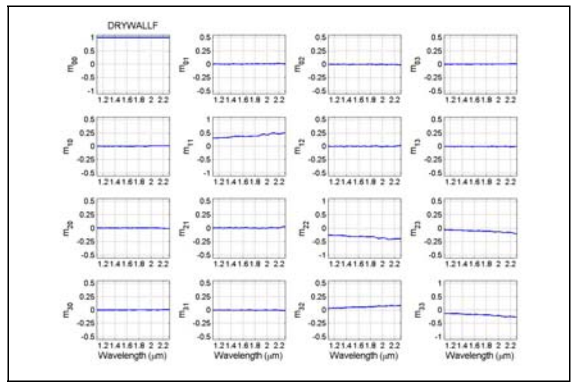
(a) rubber



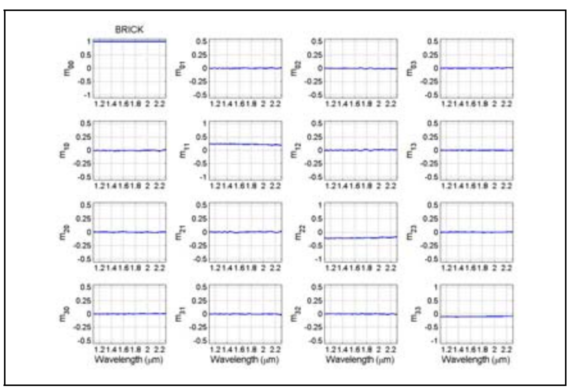
(b) shingle



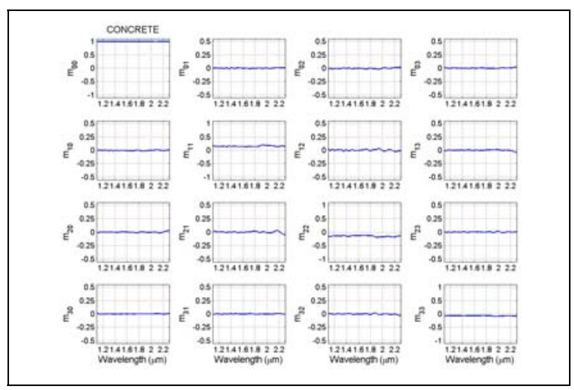
(c) plywood



(d) drywall



(e) brick



(f) concrete

Figure 6. Mueller matrices at normal incidence in SWIR band.

4. FEATURE EXTRACTION AND SEPARABILITY ANALYSIS

Object discrimination falls under the general topic of pattern recognition or pattern classification. A thorough treatment of the subject is covered by Duda, Hart, and Stork[7]. One approach to pattern classification is a feature-based technique where feature vectors are derived from the experimental measurements and functional mappings are established that will transform the vectors for each object into identifiable classes. These mappings are often called "discriminant functions" and they can be constructed in a variety of ways. For this study we implement a linear learning machine technique based on the support vector machine[8] (SVM). Let $\vec{f} = (f_1, f_2, \cdots, f_N)$ be an N element feature vector. Then a linear learning machine can be described by a discriminant function, d, that is a hyper-plane in $\Re^N$ given by

$$d(\vec{f}) = \sum_{n=1}^{N} w_n f_n + b$$

where $\vec{w} = (w_1, w_2, \cdots, w_N)$ and b are the tunable parameters. This formulation has limited applicability for problems whose features are non-linearly related. SVMs extend this approach through the introduction of a kernel, $\vec{\phi} = (\phi_1, \phi_2, \cdots, \phi_N)$. As such, non-linear measurements in the input space can be mapped into a high-dimensional linear feature space through the equation

$$d(\vec{f}) = \sum_{n=1}^{N} w_n \phi_n(\vec{f}) + b$$

In this new space, linear discriminant optimization can be employed to establish the hyper-planes that best separate the data into distinct classes or regions. SVMs are trained using a supervised learning paradigm where the entire collection of measurements is partitioned into two sets: a training set and a test set. The training set is used to derive the coefficients, $(\vec{w}, b)$, of the separating hyper-plane. Once trained, these SVMs are evaluated for classification performance, robustness and generalization via the test set.

For any feature-based approach, one of the first questions to be addressed is: What are the best features? This is a non-trivial issue and is application dependent. In our case we derive features based on the mBRDF and Mueller matrix measurements. The mBRDF is the first feature considered and we commonly call this the reflectance (ref). To derive polarimetric features, we start by consider the Lu-Chipman decomposition[9] of an experimental Mueller matrix. This method separates a Mueller matrix into three distinct factors: diattenuation, retardance, and depolarization. The diattenuation of a material is a quantifiable representation of changes to the intensity transmittances of the incident polarization states. Retardance is a representation of the phase-changing characteristics the material induces on the incident polarization. These are non-depolarizing descriptors. For this experiment, we consider retardance (ret) as a candidate feature based on the preliminary analysis of the measured data. Additionally, we have chosen to study these materials from a system's perspective. Two of the most common operational wavelengths are 1.06μm and 1.55μm. For this study, we report on the findings of a vertically polarized transmitter operating at 1.55μm. Hence, the polarization state incident upon the sample can be represented by the Stokes vector $S_I = I_0 \cdot [1\ -1\ 0\ 0]^T$ where I_0 is the total intensity of the transmit beam or pulse. We then derive the degree of polarization (dop) from the reflected Stokes vector, $S_R = M(\lambda, \theta) \cdot S_I$, where $M(\lambda, \theta)$ is the laboratory measured sample Mueller matrix which is a function of wavelength, λ = 1.55μm, and incident angle, θ. A word of caution: It has been our observation and also previously reported by others[10,11] that comparing measurement between and among systems must be exercised with care. The polarization state collected by a system appears to be dependent upon the viewing laser-speckle field, sensing geometry, and receiver collection aperture size and therefore can not be generalized to other systems without taking these factors into consideration.

In summary, we have constructed feature vectors containing the following three elements:

1. mBRDF (ref)
2. Degree of Polarization (dop)
3. Retardance (ret)

To derive the necessary training and test vectors for our SVM classifiers, we use the 18 angular measurements at 1.55μm and create Gaussian statistical models for each feature of each material. Next, 1000 samples are generated for training and testing: 20% for training, 80% for testing. Fig. 7 illustrates the statistical relationships among the six materials for this 3D feature space.

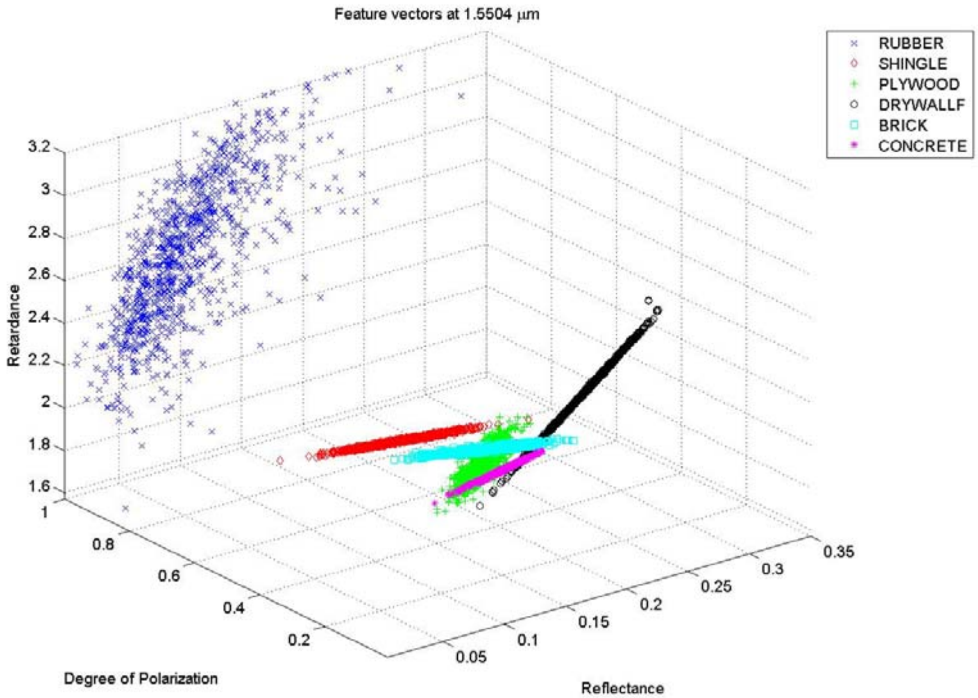


Figure 7. 3D feature space [ref, dop, ret].

Another fundamental issue is the kernel selection for the SVMs. Commonly used kernels, guidance for selecting kernels, and techniques for making kernels are described by Cristianini and Shawe-Taylor[8]. Since our data has been modeled as Gaussian processes, we selected the radial basis function (RBF). By this selection, the SVMs become Gaussian-shaped mapping functions and should separate well in the kernel mapped space. The shape of each classifier is controlled through a parameter, α, that is related to the variance of the models and the shape of the RBFs. To compare the relative separability of ref, dop, and ret, we tested all six combinations of feature vectors. Namely, we ran six experiments using the following feature vectors: [ref], [dop], [ret], [ref, dop], [ref, ret], [dop, ret], [ref, dop, ret]. SVMs are trained for each material as a two-class problem. Class 1 is the material (object) of interest and Class 0 contains all other materials. Fig. 8 shows the resulting classification system used for separability analysis.

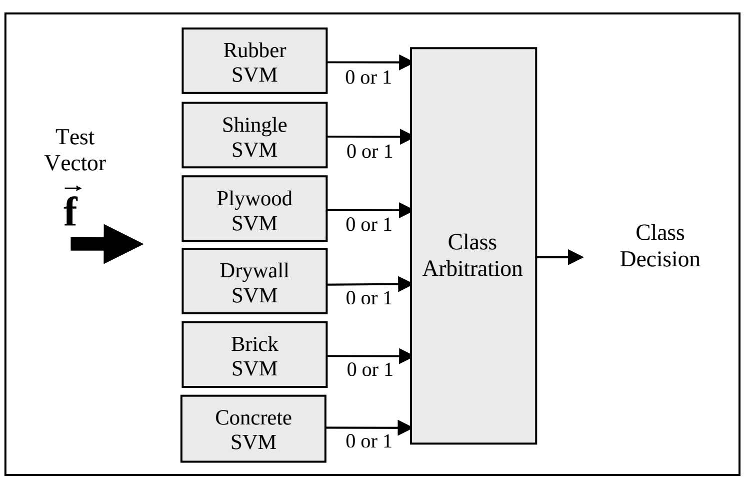
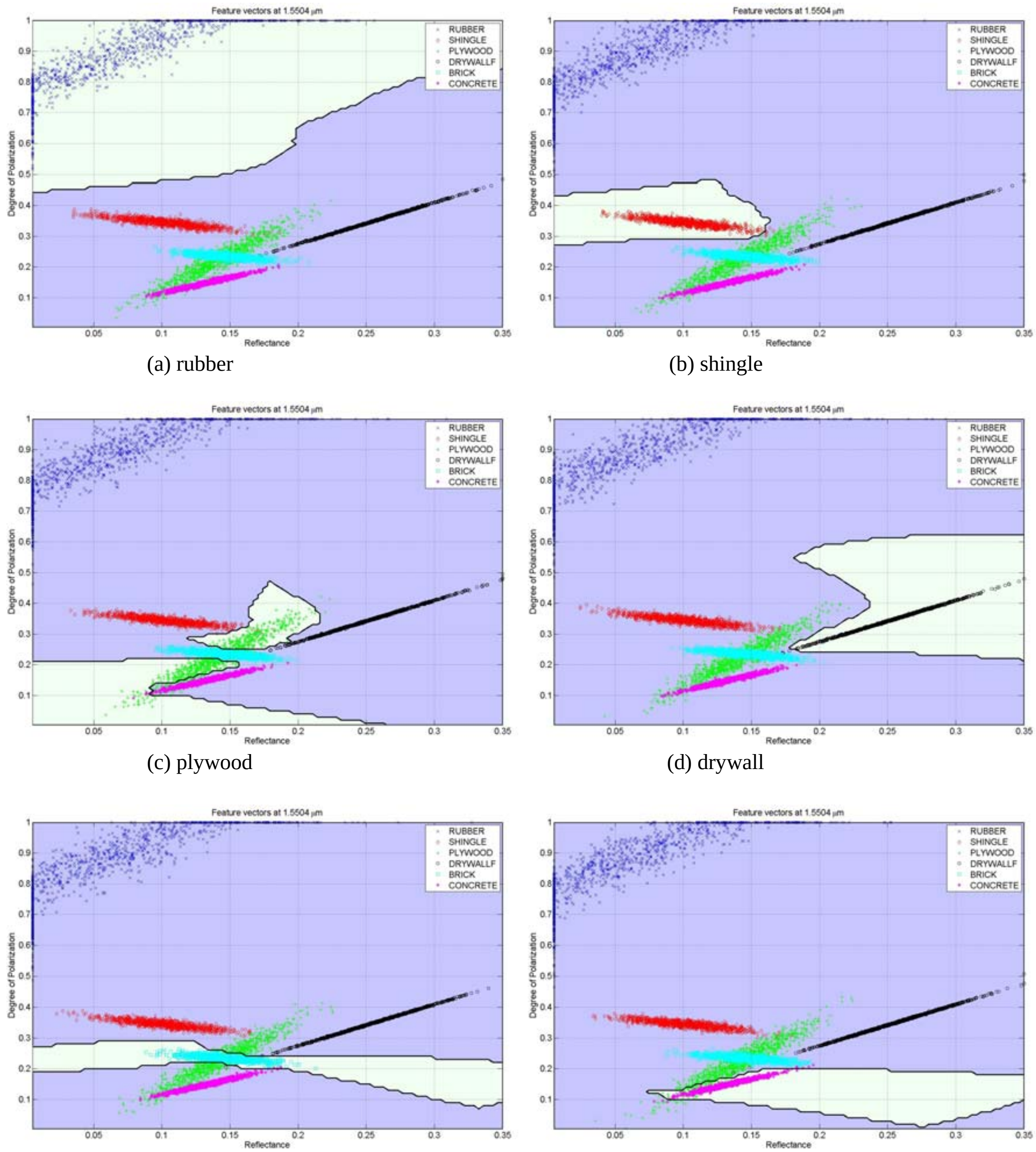


Figure 8. Material classification system.

Figure 9 shows the decision boundaries created for each material classifier using the 2D feature vector [ref, dop]. Table 1 lists the classifier performance for each material for all six experiments. Here, P_{CC} is the percent of correct classification (feature vectors of this material correctly classified) and P_{FA} is the percent of false alarms (feature vectors of other materials classified as this material). As an example, for the material "shingle" using the feature vector containing only [dop], 94% of the shingle measurements were (correctly) classified as shingle and 10% of all other material measurements were (incorrectly) classified as shingle.



(a) rubber (b) shingle

(c) plywood (d) drywall

(e) brick (f) concrete

Figure 9. Support vector machine class decision boundaries for feature set [ref, dop].

Table 1. SVM Classifier Results

Feature Vector			Classifier Results											
			Rubber		Shingle		Plywood		Drywall		Brick		Concrete	
ref	dop	ret	P_{CC}	P_{FA}	P_{CC}	P_{FA}	P_{CC}	P_{FA}	P_{CC}	P_{FA}	P_{CC}	P_{FA}	P_{CC}	P_{FA}
■			0.65	0.03	0.52	0.06	0.00	0.00	0.99	0.01	0.08	0.01	0.00	0.00
	■		1.00	0.00	0.94	0.10	0.41	0.02	0.45	0.02	0.99	0.07	0.98	0.04
		■	0.96	0.01	0.83	0.05	0.94	0.06	0.09	0.01	0.67	0.05	0.82	0.06
■	■		1.00	0.00	0.99	0.01	0.66	0.01	0.99	0.00	1.00	0.05	0.99	0.02
■		■	0.98	0.00	0.71	0.01	0.96	0.01	1.00	0.01	0.89	0.05	0.92	0.01
	■	■	1.00	0.00	1.00	0.02	0.80	0.01	0.91	0.01	1.00	0.00	0.98	0.04
■	■	■	1.00	0.00	1.00	0.00	0.89	0.00	1.00	0.00	1.00	0.00	0.99	0.02

5. CONCLUSION

In summary, the reflective and polarimetric properties of six urban materials were measured using a dual rotating retarder spectropolarimetric reflectometer. Feature vectors containing reflectance (mBRDF), retardance, and degree of polarization were derived from the measurements and used to construct statistical models of each material. These models were used to generate training and testing data for separability studies through the implementation of support vector machines. The three chosen features provided adequate separability for the materials under study and yielded a high probability of correct classification while maintaining a low number of false alarms. Future work will consider a larger database, other features, synthetic polarized imagery generated by Irma, and a more rigorous pattern recognition analysis.

REFERENCES

1. A. Rothkirch, G. Meister, B Hosgood, H. Spitzer, and J. Bienlein, “BRDF Measurements on Urban Materials Using Laser Light,” *Remote Sensing Reviews*, Vol. 19, pp. 21-35, 2000.
2. D. H. Goldstein and J. L. Cox, “Spectropolarimetric properties of vegetation,” Proc. SPIE 5432, *Polarization: Measurement, Analysis, and Remote Sensing VI*, pp. 53-62, 2005
3. J. Savage, C. Coker, B. Thai, O. Aboutalib, N. Yamaoka, and C. Kim, “Irma 5.1 Multi-Sensor Signature Prediction Model,” Proc. SPIE 5811, *Targets and Background XI: Characterization and Representations*, pp. 199-211, 2005.
4. D. H. Goldstein and D. B. Chenault, “Spectropolarimetric reflectometer,” *Opt. Eng.*41 (5), pp. 1013-1020, 2002.
5. R. M. A. Azzam, “Photopolarimetric measurement of the Mueller matrix by Fourier analysis of a single detected signal,” *Opt. Lett.* 2, (6), pp. 148-150, 1978.
6. D. B. Chenault, J. L. Pezzaniti, and R. A. Chipman, “Mueller Matrix Polarimeter Algorithms,” Proc. SPIE 1746, *Polarization Analysis and Measurement*, pp. 231-246, 1992.
7. R. O. Duda, P. E. Hart, D. G. Stork, “Pattern Classification,” Second Edition, John Wiley & Sons, Inc., 2001.
8. N. Cristianini and J. Shawe-Taylor, “An Introduction to Support Vector Machines and other kernel-based learning methods,” Cambridge University Press, 2000.
9. D. H. Goldstein, “Polarized Light,” Second Edition, Marcel Dekker, Inc., 2003.
10. J. Li, G. Yao, and L. Wang, “Degree of polarization in laser speckles from turbid media: Implications in tissue optics,” *Journal of Biomedical Optics*, Vol. 7, No. 3, pp. 307-312, 2002.
11. C. Betty, A. Fung, and J. Irons, “The Measured Polarized Bidirectional Reflectance Distribution Function of a Spectralon Calibration Target,” Proc. IGARSS, Vol. 4, pp. 2183-2185, 1996.